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Adapting climate change challenge: A new vulnerability assessment framework from the global perspective

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A R T I C L E I N F O

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A B S T R A C T

Climate change has caused worldwide concern due to its adverse effects on the global ecosystem, economy and society. In this study, a new integrated framework was proposed for assessing the national vulnerability to climate change by considering both the sensitivity and adaptive capacity. Then, a first assessment of the spatial-temporal change in national vulnerability from 1996 to 2008 was provided from the global perspective. Finally, 171 countries were grouped, and hotspots of climate change were identified. Based on the results, the earth is more vulnerable than invulnerable, and the average rate of increase in the vulnerability index from 1996 to 2008 was 0.30%. African countries were identified as hotspots of vulnerability and instability in the changing climate, and 8 groups were clustered based on the key influencing index of 171 countries. The results of this new framework are consistent with the previous Fragile State Index and World Risk Index but provide more details and quantitative vulnerability analysis. The methods and results presented in this paper could be used as references for climate change adaption and policy at the global scale.

1. Introduction

Understanding, estimating and mitigating the impacts of global changes such as climate warming and extreme weather intensification poses one of the most crucial and challenging issues of this century. Climate change is likely to cause impacts on a large number of economic, societal and ecological services directly or in synergy with other processes, and these impacts can vary strongly by country. Evidence-focused studies have reported that recent extreme weather conditions have resulted in reduced freshwater availability, resource depletion and energy shortage (Theisen et al., 2013), while several emerging studies have also reported that climate change has increased food shortage, social unrest, local skirmishes and even wars (Castree, 2010). Thus, comprehensive insight into the likely impacts of climate change and its temporal-spatial variability among countries would provide information for collaboration to design effective conservation strategies that mitigate climate-driven loss.

Knowledge of national vulnerability provides prerequisites and common countermeasures for climate change adaptation (Feng and Chang-Le, 2014; Fish et al., 2008; Tol, 2018). Vulnerability, as described during the last 20 years (Kobak et al., 1996), is generally defined as the ability of individuals and social groups to respond to or adapt to external pressures (Smit and Wandel, 2006). Specifically, the Intergovernmental Panel on Climate Change (IPCC) defined vulnerability as "the degree to which a system is susceptible to, and unable to cope with adverse effects of climate change, including climate variability and extremes." (Parry, 2007). Typical vulnerability analysis involves three steps, covering the stress to which a system is exposed, its sensitivity, and then its adaptation. Sensitivity represents the degree to which a system could be modified or affected by perturbations, while as an extensional concept, adaptability is defined by the IPCC as "the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities." Adaptation is the evolving ability of a system to accommodate environmental hazards or policy change and to expand the range of variability with which it can cope (Adger, 2006; Filho et al., 2018; Zhang et al., 2018). The common purpose of adaptability analysis is to estimate how the impact of climate change can be mitigated or offset by ability "to adapt to the impact" (or "to reduce") (Parry, 2002). Previous studies have revealed the vulnerability of different subjects to climate change,

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including mammals (Pacifici et al., 2018), areas like the Amazon (Boulton et al., 2017), soil (Hursh et al., 2017), extreme events, watersheds, elevation levels, latitudinal belts, flood plains, wetlands, coastal zones, types and extent of agriculture, physiographic zones. However, the assessment of vulnerability to climate change is not fully understood at the global scale, and knowledge of the spatial-temporal variability in national vulnerability is limited but is very important for policy recommendations.

Additionally, the Environmental Vulnerability Index (EVI) has been proposed to measure national environmental problems in a changing world (Pandve et al., 2011), while studies have also added several corresponding indexes in obtain quantitative evaluation of environmental vulnerability for the first time (Pandve et al., 2011). Moss et al. (2001) earlier proposed an aggregation analysis of the importance of indexes in quantifying the vulnerability of countries to climate change. Since then, the assessment framework of vulnerability has been widely discussed. In the study by Nd TB (2003), the vulnerability framework was developed into a comprehensive Index framework suggestion. After that, many institutions and scholars have used the national vulnerability assessment framework—for example, IPCC has proposed special reports on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. At the same time, the Peace Fund proposed the Fragile States Index in 2006 for assessing national vulnerability, or the possibility of conflict or collapse at the country scale. Currently, the Fragile States Index rankings have incorporated social, economic and political dimensions (more information could be found from the website of http://global.fundforpeace.org/index.php). Meanwhile, researchers have provided detailed analyses of adaptive indexes. Zhang (2015) mentioned the national security of climate change, which includes 11 kinds of indexes, covering political security, homeland security, military security, economic security, cultural security, social security, technology security, information security, ecological security, resource security and nuclear safety. The National Policy Assessment System, which has been applied to Africa by the World Bank, includes economic management, structural policies, social inclusion and policy equity, public sector management and institutional management (more details could be found from the website of http://datatopics.worldbank.org/cpia/). However, it should be noted that with these frameworks, different index frameworks and analytical methods would result in different vulnerability assessments (Krishnamurthy et al., 2014). Recent national-scale vulnerability assessments seldom focus on the climate change impact with consideration of extreme disasters and the society substructure. A new integrated assessment framework based on recent studies is lacking at the national scale. Additionally, due to the adaption of the changing world, the fragility and sensitivity of each country to climate change are changing due to adaption efforts. The establishment of the spatial-temporal variability of national vulnerability and related hotspots should be paid great attention.

In this sense, this paper focused on the following objectives: i) an integrated framework was proposed by considering both sensitivity and adaptation, and ii) a first assessment of the spatial-temporal change in national vulnerability and hotspots was provided from the global perspective.

2. Materials and methods

2.1. Index framework construction

In this study, an integrated index framework was developed for the vulnerability framework for climate change at the global scale. This index framework is based on the analytic hierarchy process (AHP) method, covering a total of 22 indexes to provide a comprehensive evaluation of climate change impact. Three layers, including the system layer, structure layer and datum layer, are considered by the AHP, which was developed by Saaty (1986) as a multicriteria decision analysis method that relates to multiple criteria decision-making (MCDM). For the system layer, 22 indexes were first divided into national sensitivity and adaptation indexes. Then, for the structure layer, several direct climate indexes, such as daily temperature, precipitation and extreme events, were selected as the sensitivity indexes, while national economic security, social security, political security and ecological security were considered as the adaptation indexes.

Typically, the exposure, sensitivity and adaptation of each system are considered for vulnerability assessment. Exposure characterizes the contact degree of events and stresses (Moss et al., 2001; Wu et al., 2017), and many communities have developed their own conceptual exposure models at the local scale (Abebe et al., 2018). However, exposure indexes are hard to consider at the national scale, not only because the contribution of temperatures and precipitation varies among countries but also because it is hard to judge the negative or positive impact of exposure (Cozannet et al., 2013). Thus, this integrated index framework mainly focused on the sensitivity and adaptation of each country to the climate change conditions. On one hand, sensitivity indicates the positive or negative impacts of climate change on each country, which are determined by the type of exposure and systematic features. The national sensitivity could be assessed based on historical data collection, repeated natural surveys and other publications. In this study, sensitivity indexes were divided into daily temperature and precipitation, as well as extreme events (Berkes and Folke, 1998). By considering the suggested essential elements for expanded vulnerability analysis (Nd et al., 2003) and the attribute(s) of the coupled system (Soares et al., 2012), the Miami Index was used for quantifying the integrated impacts of temperature and precipitation. This index, proposed by several studies (Heltberg and Bonchosmolovskiy, 2011; Jin and Chen, 2018), represents the primary productivity empirical formula by collecting a total of 53 typical biological production measurements around the world (Nd et al., 2003). The extreme event index was expressed as the number of people affected by extreme disasters and the number of people who died during extreme disasters. Specifically, the Miami Index is expressed as:

$$y = \min\left\{\frac{3000}{1+\exp(1.42-0.141t)}, 3000(1-\exp(-0.00065p))\right\} \tag{1}$$

in which t is the annual average temperature and p is the annual precipitation.

Adaptation means the capacity of a system to adapt to or minimize any potential loss from climate change. Through a literature review and consideration of data availability, the adaptation indexes were constructed by including economic, political, social and ecological security. The economic security means having a stable income or other resource to support a living standard in the foreseeable future. Tol (2018) pointed out that the economic index for climate change includes the costs of abatement and of climate change. In addition, Zhang et al. (2015) suggested that national trade and people's income would also be a factor. Thus, the economic security in this article includes per capita economic data (GDP per capita and per capita income), international trade data (trade balance) and tertiary industry proportions (gross industrial product showed the abatement's costs and ratio of agricultural GDP). Climate change has also caused regional conflicts, which

mainly depend on the gender index and political security (Nagel, 2015). World Bank statistics were adopted for these indexes, which were called the Worldwide Governance Index (WGI) project. The governance was defined as an organization which consists of the traditions and institutions by which authority in a country is exercised. Six indexes were used to describe political security, including voice and accountability, political stability with no violence, government effectiveness, regulatory quality, rule of law, and control of corruption. Disaster management by countries and their citizens is an important part in accommodating climate change (Urry, 2011). Social security was divided into four aspects, including population (population density and growth rate of the population), education (primary school completion rate), gender equality (gender index, expressed as the ratio of boys to girls in primary schools), and refugees and the homeless. To fit the normal distribution, the population density, homeless rate and GDP data were converted by logarithm transformation. The ecological security to climate change covers many parts (Jr, 2001), as it refers to the health and integrity of the ecosystem, which was expressed by freshwater resource per capita, the forest coverage rate, natural resources and the percent of agricultural land. The detailed index framework can be found in Table 1, while the statistical data of each index were collected from the Climatic Research Unit and the International Disasters Database, as well as websites of the World Bank and the Worldwide Governance Index.

To cover the temporal variability of national vulnerability, the period from 1996 to 2008 was selected for each country because more detailed data were found for this period, especially for the political security index from the Worldwide Governance Index that begun in 1996, and the impacts of extreme events were lacking after 2008. Specifically, some scarce data points were generated by the nearest neighbourhood algorithm (Monnereau et al., 2017). First, the Euclidean distance between the scarce data series and other data series was calculated by the following equation:

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{2}$$

Second, all distances between scarce data series and other data

Table 1
Summary of components and indexes used for the vulnerability index, including the weight of each index.

System layer	Structure layer	Datum layer	Quantitative index	Weight	Data source
Sensitivity index	Daily temperature and precipitation	The impact of temperature and precipitation	Miami Index	1.11E-01	Climatic Research Unit
	Extreme events	The impact of extreme events	Percentage of people affected*	8.04E-02	The International Disasters Database
			Percentage of people who died*	5.85E-02	
Adaptation index	Economic security	Economic security	GDP per capita *	2.30E-02	World Bank Open Data
			Per capita income *	5.00E-03	
		International trade	Balance of trade *	1.33E-02	
		Tertiary industry proportion	Gross industrial product	2.46E-01	
			Ratio of agricultural GDP	3.71E-02	
	Political security	Voice and Accountability		1.02E-01	Worldwide Governance Index
		Political Stability with No Violence		1.02E-01	
		Government Effectiveness		1.02E-01	
		Regulatory Quality		1.02E-01	
		Rule of Law		1.02E-01	
		Control of Corruption		1.02E-01	
	Social security	Population	Population density *	3.01E-02	World Bank Open Data
			Growth rate of population	2.90E-02	
		Education	Primary school completion rate	2.20E-02	
		Gender equality	Gender index	1.53E-02	
		Refugees and the homeless	Homeless *	1.16E-02	
	Ecological security	Water	Freshwater resources per capita	7.84E-02	World Bank Open Data
		Forest	Forest coverage rate	5.62E-03	
		Biodiversity	Natural resources	8.79E-03	
		Land	Agricultural land	1.23E-01	

Note: * The data logarithm was processed. More data could be found from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_3.23/crucy.1506241137.v3.23/countries/and http://www.emdat.be/database.

series were ranked, and the smallest k samples were chosen to calculate their average value for interpolating the scarce data value. Using cross-validation, k was calculated as 7 in this study. Specifically, the national annual average temperature and precipitation data from the Climatic Research Unit were used to calculate the Miami Index from 1996 to 2008 for each country. The percentages of people affected by and who died from extreme events were collected from the International Disasters Database, while all data on political security were from the Worldwide Governance Index.

2.2. Calculation of the vulnerability index

The flowchart of the national vulnerability index is found in Fig. 1. To provide a comprehensive evaluation, the entropy weight and AHP methods were used. The information entropy, introduced by Shannon (Shannon, 1948), is defined as the average amount of information produced by a stochastic source of data. A greater information entropy indicates higher disorder and a smaller utility value of each index. First, the index value was standardized by the following equations:

$$\text{For positive indexes:} Y_{ij} = \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \times 100 \tag{3}$$

$$\text{For negative indexes:} Y_{ij} = \frac{\max(X_i) - X_{ij}}{\max(X_i) - \min(X_i)} \times 100 \tag{4}$$

After the standardizing process, a matrix X indicated the vulnerability value for a country, while X_i indicated the standardized value of each index. For each index, the maximum and minimum values of a country are 100 and 0, respectively.

Then, the information entropy of each index was calculated:

$$E_j = -\ln\frac{1}{n}\sum_{i=1}^{n}\frac{Y_{ij}}{\sum\limits_{i=1}^{n}Y_{ij}}\ln\frac{Y_{ij}}{\sum\limits_{i=1}^{n}Y_{ij}} \tag{5}$$

In the formula, n means the sample size. If $Y_{ij} = 0$, define $\ln\frac{Y_{ij}}{\sum_{i=1}^{n}Y_{ij}} = 0$. Finally, the weight of information entropy was obtained by the following equation:

$$W_j = \frac{1 - E_i}{k - \sum E_i} \tag{6}$$

which is an objective weight of the indexes. In formula (5), k means the number of variables.

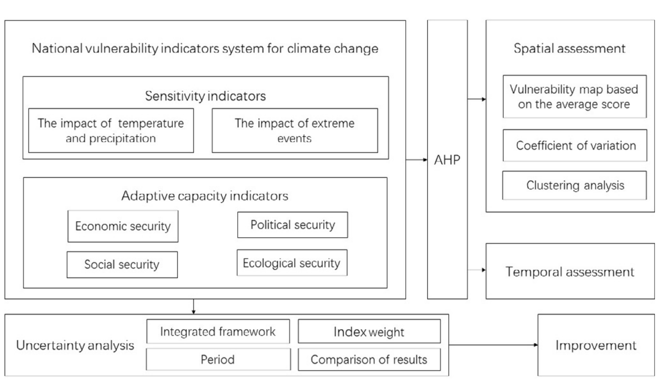

Fig. 1. Research system and process.

However, the dispersion of the data set might not reflect the importance of indexes, so that they may take on unreasonable weights in the assessment. For example, some indexes take up a large proportion of the model, such as the gross industrial product, agricultural land and Miami Index, while some take up a small proportion of the model, such as the gender index, per capita income, balance of trade and freshwater resources per capita. Thus, a judgement matrix index was also constructed to measure the importance between two indexes. By calculating the geometric mean of each row and normalising the vector G_j, the weight was generated for the AHP.

$$G_j = \sqrt[n]{\prod_{i=1}^{N} X_{ij}} \tag{7}$$

Adopting the principle of correspondence between subjectivity and objectivity, the final weight of all 22 indexes was obtained:

$$WG_i = \frac{W_i G_i}{\sum W_i G_i} \tag{8}$$

Weights of higher indexes were decided by an additive process of the weights of lower indexes. R software (version 3.4.0, New Zealand) was used for model building and calculation.

2.3. Identification of the key index

To identify the key influencing index, the contribution of each index to the national vulnerability was quantified, and the 171 countries in this study were grouped by adaptive countermeasures. The clustering analysis was used to describe the degree of similarity between countries to verify the hypothesis and reduce information loss. SAS software (version 9.4, SAS Institute, Cary, North Carolina, USAs) was used for the clustering process. In this study, Ward's method was used for grouping the countries, and a final eight clusters, which were determined by Pseudo F and Pseudo T-Squared methods, were generated by the following equation:

$$D(G_1, G_2) = \sum_{x\in G_1\cup G_2}(x_i - \bar{x})^T(x_i - \bar{x}) - \sum_{x\in G_1}\left(x_i - \overline{x_1}\right)^T\left(x_i - \overline{x_1}\right) - \sum_{x\in G_2}\left(x_i - \overline{x_2}\right)^T\left(x_i - \overline{x_2}\right) \tag{9}$$

2.4. Temporal and spatial analysis

Using the AHP and entropy weight, a vulnerability index from 1996 to 2008 was assigned for each country. Then, the temporal variability of the national vulnerability was expressed by the coefficient of variation in the index from 1996 to 2008, and all 171 countries were grouped as relatively unstable, neutral, and relatively stable, based on the three-digit number and three approximately equal groups. Then, the average value of the vulnerability index from 1996 to 2008 was also calculated to identify the spatial distribution of the national vulnerability and the hotspots of countries vulnerable to climate change were identified using the geographic information system at the global scale. According to the mean values of vulnerability index, the 171 countries were then grouped as relatively invulnerable, neutral, and relatively vulnerable. Cluster results also helped identify similarities between fragile countries based on the identification of the key influencing index.

2.5. Uncertainty analysis of the results

It should be noted that uncertainty did exist for the analysis results, and the main uncertainty might have come from the subjective weight decided by the AHP. To quantify the uncertainty of the result, the Monte Carlo method was used to adjust the judgement matrix by repeated sampling from the weight error range, and a definitive description of the problem was approximated by generating drawings from a probability distribution (Kroese and Chan, 2014). For each of the three indexes, if $a_{ij} = k_1(k_1 > 0), a_{jk} = k_2(k_2 > 0)$, the following equation was defined to yield a reciprocal, but not consistent, judgement matrix. This was because it is difficult to make a matrix element to be an integer or the reciprocal of an integer if the matrix is limited to a consistent matrix:

$$a_{ik} = k_1 + k_2 - 1 \tag{10}$$

Thus, it was assumed that the relationship of importance was linear. By generating the Monte Carlo random number and judgement matrix, it was easy to determine the approximate scope of weight of each index. By sorting the Monte Carlo results, a 90% confidence interval could be extracted. R software (version 3.4.0, New Zealand) was used for this Monte Carlo simulation. The intervals of 18 indexes were generated and shown in Table 2.

3. Results and discussion

3.1. Spatial variability results

The mean value and coefficient of variation in vulnerability index from 1996 to 2008 were calculated for each country and are shown in Fig. 2. It is clear that the mean value of vulnerability index varied from country to country in the range of 26.51–62.88, with the mean value being 42.83. Under climate change, the most vulnerable and least vulnerable countries were identified as Liberia and Denmark, respectively. Most African countries fell within the range of 40–60, indicating that African countries are more vulnerable than other continents to the changing climate. This may be because many African countries are suffering drought and relatively poor financial conditions, which were identified as key influencing indexes of the vulnerability of Africa. The most invulnerable country in Africa was identified as Gabon, whose mean index value was 29.15. West and Southeast Asia are also relatively vulnerable regions, with the index values being approximately 40 and some countries even reaching 50. Iraq and Kazakhstan were the countries with highest and lowest scores in these two areas, which were 59.81and 37.52, respectively.

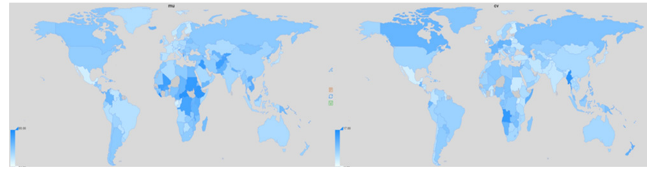

Fig. 2. The left graph shows the average of the 13-year vulnerability index for 171 countries. The darker the colour is, the larger the index and the higher the vulnerability. The right graph shows the coefficient of variation of the 13-year vulnerability index for 171 countries. The darker the colour is, the larger the coefficient and the higher the volatility.

The coefficient of variation during the 13 years also varied by country. Additionally, the mean standard deviation and coefficient of variation in all 171 countries were 7.61 and 7.13E-02, respectively. These values were multiplied by 100 to provide a clearer comparison, as these values were relatively small. As shown in Fig. 2, the coefficients of variation of some costal countries were over 10.00 compared to a global average value approximately 7.00. This obvious temporal variability could be explained by the fact that costal countries may suffer from tsunamis, which are low in frequency but would have great impacts on the national vulnerability. Thus, costal countries that suffered from tsunamis would show higher coefficients of variation, indicating that coastal countries are relatively unstable in the changing climate. In this study, Myanmar was identified as the most unstable country, whose coefficient of variation value was the largest (15.85), while Lithuania was the most stable country, whose index value was the lowest (2.06). For other areas, the vulnerability index value was uneven among countries.

As mentioned above, countries could be grouped as relatively unstable, neutral, and relatively stable and as relatively invulnerable, neutral, and relatively vulnerable based on the coefficients of variation and mean values of the national vulnerability index, respectively. Finally, these 171 were divided into 9 groups based on cross-validation, which can be found in Fig. 3. African countries such as the Central African Republic were the most relatively vulnerable and unstable countries. Relatively vulnerable and neutral stable countries such as Iraq were mostly in areas of

Table 2
90% confidence intervals for the range of weights of 18 indicators.

Indexes	Intervals	
	5% boundary	95% boundary
GDP per capita	5.00E-03	8.43E-02
Per capita income	1.15E-03	2.06E-02
Balance of trade	2.84E-03	4.94E-02
Gross industrial product	2.99E-02	3.57E-01
Ratio of agricultural GDP	2.37E-02	3.07E-01
Political index	1.22E-01	2.34E-01
Population density	2.98E-03	5.18E-02
Growth rate of population	5.55E-03	9.27E-02
Primary school completion rate	7.40E-03	1.20E-01
Gender index	1.06E-02	1.65E-01
Homelessness	4.95E-03	8.34E-02
Forest coverage rate	7.28E-03	1.18E-01
Freshwater resources per capita	5.52E-04	9.97E-03
Natural resources	1.77E-03	3.12E-02
Agricultural land	1.05E-02	1.64E-01
Miami Index	1.11E-02	1.71E-01
Number of people affected by extreme disasters	1.44E-02	2.12E-01
Number of people died from extreme disasters	1.01E-02	1.59E-01

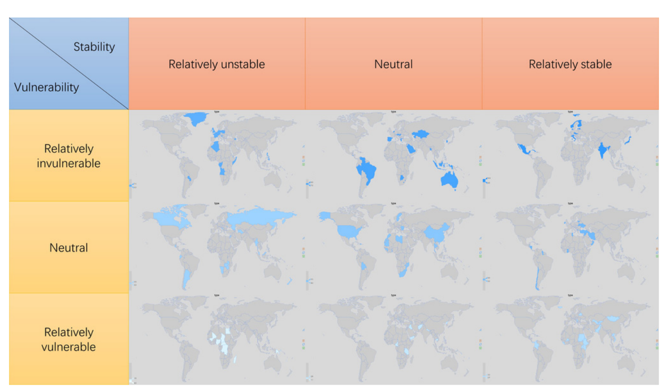

Fig. 3. Countries were divided into the following three categories based on the averages of the 13-year vulnerability index: relatively invulnerable, neutral, and relatively vulnerable. Countries were also classified into the following three categories by the coefficients of variation of the 13-year vulnerability index: relatively unstable, neutral, and relatively stable. Integrating the two classification methods divided all countries into 9 categories.

suffering war. Relatively vulnerable and stable countries such as Pakistan were mostly coastal countries in Asia and Africa. Neutrally vulnerable and relatively unstable countries such as Canada were mostly in middle or high latitudes. Neutrally vulnerable and neutral stable countries such as China mostly had relatively large territorial areas. Neutrally vulnerable and relatively stable countries were mostly West Asian and Eastern European coastal countries such as Turkey. Relatively invulnerable and unstable countries such as France were mostly in the northern hemisphere, with a relatively random distribution. Relatively invulnerable and neutral stable countries such as Australia were mostly large coastal countries. Relatively invulnerable and stable countries were mostly developed countries in northern hemisphere such as Norway. Thus, African countries were identified as hotspots of vulnerability to the changing climate.

Furthermore, countries were also clustered based on the contributing rate of each index to the national vulnerability. As shown in Fig. 4 and Fig. 5. They were separately named relatively natural and political unsteady, relatively low productivity, relatively low GDP, relatively strong economic, relatively developed, relatively developed industry and little resources, relatively abundant natural resources and lesser population, middle latitudes with larger lands countries.

The first class named relatively natural and political unsteady countries that suffered from extreme disasters and political weakness were Fiji and Sudan. This cluster's scores for the number of people affected by extreme disasters and the number of people who died from extreme disasters were significantly higher than those of other clusters. Their average political index scores were the highest of all clusters. For example, Fiji's mean value of people who died from extreme disasters and political index were 72.69 and 66.29, compared to 46.23 and 50.46 at the global scale.

The representative countries relatively low productivity with low primary natural productivity and high population growth were America and South Africa. Their Miami Index scores were the highest, and their scores of population growth rate were the lowest. This kind of country was mostly in the temperate zone by geographical distribution. For example, America's mean value of the Miami Index and population growth rate were 64.72 and 37.31, compared to 52.36 and 50.46 at the global scale.

The representative relatively low GDP countries with high primary natural productivity, low GDP per capita and a low homeless rate were Peru and Bolivia. Their index values were the lowest for the Miami Index, with the highest value of per capita GDP and the lowest value of the homelessness index. This kind of country was mostly concentrated in the coastal areas of Latin America. Peru's mean value of the Miami Index, per capita GDP and homelessness index were 10.73, 66.29 and 44.05, compared to 52.36, 53.39 and 60.72 at the global scale.

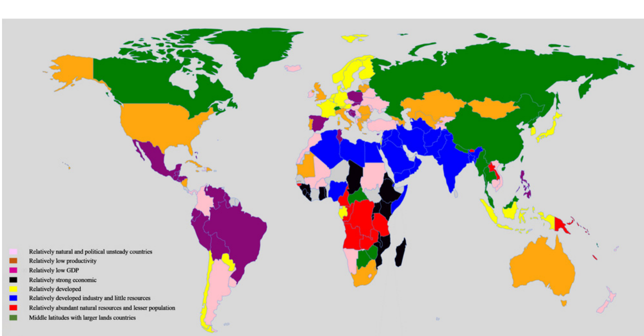

Fig. 4. National clustering results (8 categories, different colours represent different categories).

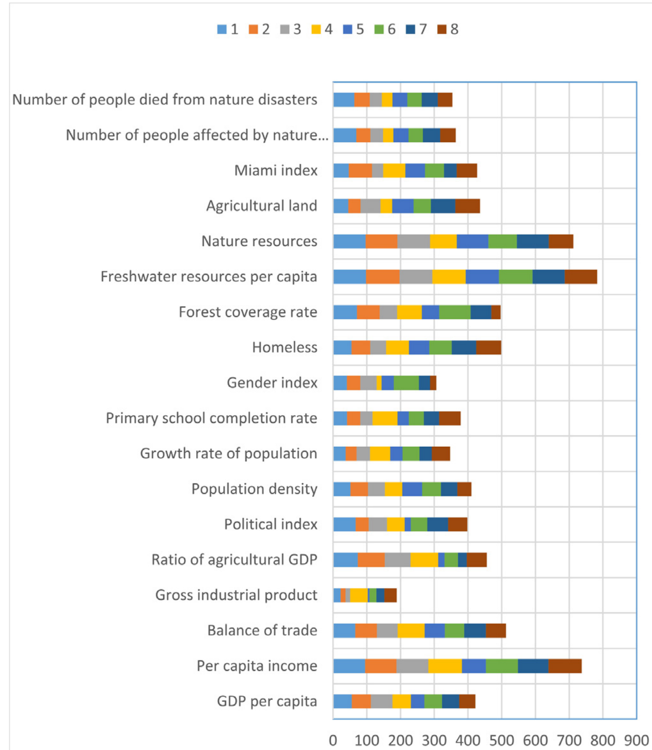

Fig. 5. Average scores of each indicator in each category in 8 categories.

The representative relatively strong economic countries were Uganda and Chad, which were affected little by extreme disasters. Their values of per capita income were low, and their industrial gross scores and values of agricultural GDP accounted were high. Their trade balance, rate of population increase and highest primary school completion rate were the highest, and their agricultural land score, number of deaths, and extreme disaster effects were the lowest. These kinds of countries were mostly in Africa. For example, Uganda's mean value of per capita income, gross industrial product, ratio of agricultural GDP, trade balance, rate of population increase, primary school completion rate, agricultural land, percentage of people affected by extreme disasters and percentage of people who died were 99.85%, 74.58, 41.41, 85.70, 63.83, 68.53, 24.19, 12.96 and 19.07, respectively, compared to the corresponding global scale results of 92.13%, 63.76, 21.73, 58.37, 41.84, 44.94, 52.36, 47.63 and 46.23.

The representative relatively developed countries were Denmark and Norway. Their values of GDP per capita, per capita income, agricultural GDP ratio, trade balance, political index, and primary school completion rate were all the lowest. This kind of country was mostly in coastal areas with small land areas. For example, Denmark's mean value of GDP per capita, per capita income, agricultural GDP ratio, trade balance, political index, and primary school completion rate were 39.95, 63.93, 2.80, 13.17, 1.49 and 29.08, respectively, compared to 53.39, 92.13, 21.73, 58.37, 50.46 and 44.94 at the global scale.

The representative countries with relatively developed industry and little resources were India and Pakistan. The index showed the lowest scores of industrial production and the highest scores of gender index, forest coverage and per capita freshwater resources. This kind of country was geographically located in western Asia, the Middle East and North Africa. For example, India's mean value of industrial production, gender index, forest coverage and per capita

freshwater resources were 59.01, 70.73, 74.69 and 99.89, respectively, compared to 63.75, 41.50, 65.52 and 98.03 at the global scale.

The representative countries with relatively abundant natural resources and lesser population were Tanzania and Zambia. In terms of indicators, their population density, the resource score and forest coverage rate were the lowest, while their homelessness and agricultural land scores were the highest. This kind of country was geographically concentrated in central and southern Africa. For example, Tanzania's mean value of population density, homeless, forest coverage rate, resources and agricultural land were 48.21, 89.94, 34.73, 99.46 and 54.33, compared to 51.92, 60.72, 65.52, 90.67 and 52.36 at the global scale.

The final representative countries middle latitudes with larger lands were geographically distributed mainly in the middle latitudes with larger lands, such as China, Canada and Russia. This kind of country had middle scores of each index.

Using the coefficient of variation of the vulnerability index also helps to determine policy proposals in terms of both stability and vulnerability in the changing climate.

3.2. Temporal variability results

The temporal trend of the global average vulnerability index from 1996 to 2008 is shown in Fig. 6. It is easy to see that the total score of all countries each year increased from 6997.95 to 7566.20 between 1996 and 2001 but decreased to 7250.34 from 2002 to 2008. The highest increasing rate appeared in 1997, which was 3.38%, and the highest decreasing rate appeared in 2006, which was 2.96%. In the increasing process, the average increasing rate was 1.57%, and in the decreasing process, the average decreasing rate was 0.6%. The increasing trend from 1996 to 2001 might have been because of the influence of the 1997 Asia financial crises, while the turning point approximately 2001 might have been because the September 11 attacks impacted economic aspects and the number of people died from extreme disasters was relatively low.

The average increasing rate from 1996 to 2008 was 0.30%, indicating that the earth gained more vulnerability than invulnerability since 1996 (see Fig. 7). From the perspective of each index, it is clear that most of the indexes were relatively stable, and only some indexes fluctuated during this period. For example, the ratio of agricultural GDP to forest coverage rate fluctuated between 10000 and 11200. However, the balance of the trade index significantly rose during 1997 due to the Asia financial crises. There also are some relationships between different indicators. The reference show some species are particularly sensitivity to temperature change (Williams et al., 2007). Thus, the related indicator explained

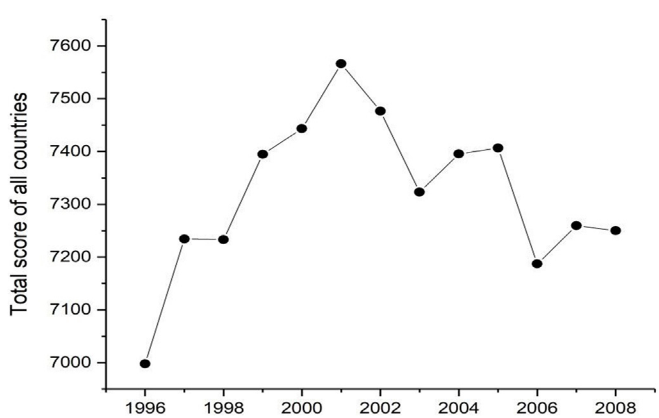

Fig. 6. Sum of the vulnerability indexes of 171 countries each year to produce a 13-year trend.

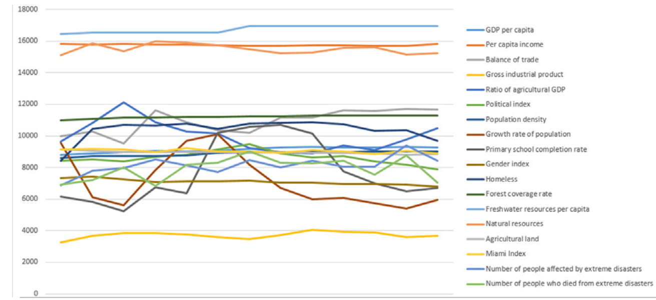

Fig. 7. Sum of the scores of all countries for each index, yielding the trend of the total score of each index over 13 years.

the fluctuation of ecological security. The crops or agriculture performance are related to the extreme event, and it has an impact chain to food safety, social security and agricultural GDP etc. (Challinor et al., 2018). The precipitation influenced on the land use configuration of land use within watershed so that the forest coverage rate and agricultural land may also change (Suttles Kelly et al., 2018).

The 171 countries could be divided into 4 grades based on the temporal vulnerability of the indexes from 1997 to 2010. These grouping results and the related influencing indexes are provided in Fig. 8 and Table 3.

To prove the reliability of the results, this article also compared the results with the World Risk Index (http://weltrisikobericht.de/english/). The World Risk Index calculates the risk for 171 countries worldwide on the basis of components including climate change. Specifically, both methods noted that the regions with the highest stability are all concentrated in Europe, and the sharp fluctuations and imbalances in Africa identified by both methods are also consistent. Although there is a time lag in the results, the vulnerability results were still quite consistent, indicating the rationality of the proposed framework. In this sense, this new index framework could be judged reliable compared with the World Risk Index but could provide more details from the cluster analysis from the temporal perspective.

3.3. Results reliability

In this study, the new vulnerability framework emphasized the sensitivity and adaptive capacity to climate change from the global perspective (Füssel, 2007). This approach and the resulting ranking of country-by-country vulnerability is useful when considering investment in adaptation strategies. Furthermore, the information contained within the analysis could be used to further hone

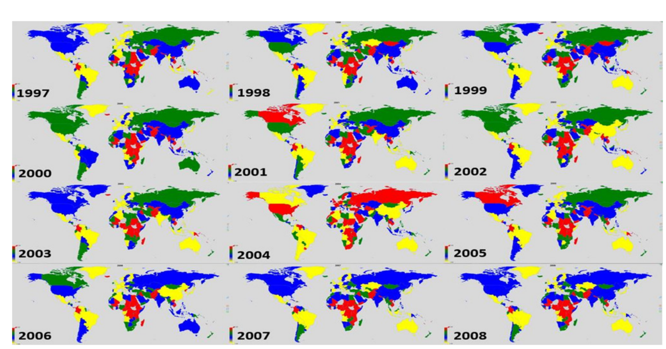

Fig. 8. National vulnerability classification (4 categories) and changes (1997–2008). The vulnerability of 171 countries was divided into 4 grades, which are shown based on colour (red > green > blue > yellow).

Table 3
Changes in the vulnerability and stability of different regions from 1997 to 2008 and their indicators.

	1997–2008 The overall sense of vulnerability	1997–2008 Vulnerability fluctuations and trends	Indicator characteristics
North America	Middle vulnerability.	Larger vulnerability in 2001 and 2005, with large fluctuations during this period.	High latitude, significant climate change (rising sea level, hurricanes), slow economic development.
South America	Relatively vulnerable, with the north being more vulnerable.	The north was more stable than the south.	Brazil's Amazon Rainforest and Chile's long coastline were significantly affected by climate change.
East Asia	Relatively vulnerable, except China.	Small-scale fluctuations.	Regional economic development was uneven, with local areas facing the sea subject to significant climate change.
West Asia	Regional differences, relatively vulnerable.	Relatively unstable, vulnerability had a slowing trend.	In some areas, political instability and low economic level.
Europe	Relatively invulnerable.	Relatively stable with no large fluctuation.	Climate change was stable, political stability, and high economic standards.
Africa	Has always been a gathering place for vulnerable countries.	Regional volatility was large and vulnerability was intensifying.	The impact of climate change can hardly be balanced in time, coupled with social turmoil and backward economic development.
Oceania	Relatively invulnerable.	Relatively stable, vulnerability was still decreasing.	Mainly affected by gradual climate change (rising sea level).

funding and investment to reduce sensitivity and/or increase adaptive capacity. In addition, this approach could be used to track vulnerability overtime, thereby assessing the outcome of efforts to increase adaptive capacity at a national level. It provides important information to understand how and why vulnerability is shifting in space and time.

The national-scale vulnerability results could be judged consistent with other previous results of national states, such as agreement in the determination of the most fragile states, as indicated by the Fragile State Index (http://fundforpeace.org/fsi/data/) and World Risk Index. Additionally, Europe's risk index was identified as stable by both methods. However, due to differences in the structures of the framework, the selection of indexes, and the assignment of weights, there were certainly differences between these methods. For example, our results indicated that the vulnerability of Mexico was lower than did previous studies, and there was also inconsistency of the vulnerability levels in some regions. This might have been because the Miami Index and two extreme disaster indexes were considered, and Mexico had low scores in these three indexes, which were 19.85 (global 52.88), 11.48 (global 47.63) and 12.13 (global 46.22), respectively. This study highlights the usage of both sensitivity and adaption indexes in the vulnerability analysis of climate change.

The national-scale vulnerability results were consistent with other previous results of climate change vulnerability indicators. Samson et al. (2011) investigated the relationship between the human population density and climate, and predicted strongly negative impacts of climate change in Central America, central South America, the Arabian Peninsula, Southeast Asia and much of Africa. Ehrhart et al. (2008) used the World Bank hazard hotspots to figure out Africa, revealing particularly the Sahel, Horn of Africa and Central Africa, central and South Asia, and Southeast Asia would have specific hazards associated with climate change vulnerability. Fraser et al. (2013) mapped drought vulnerability hotspots of wheat and maize, and their results showed most of South America, the U.S. mid-West, Southern Africa, the Mediterranean Basin, Central Asia, western China, and Australia are deemed vulnerable to declines of growing season soil moisture availability. These results of previous studies are mostly consistent with our results, indicating a reliable assessment of this study. Also, our comprehensive assessment framework provides more detailed information.

In this study, the entropy weight method was based on objective data, while AHP is based on subjective judgement. Thus, the Monte Carlo method was used to reduce the subjective factors by simulating the judgement matrix. By finding the most important index and generating random numbers to fill one row of the judgement matrix, a certain judgement matrix was produced after derivation, and the final weight was calculated. After repeating this process 10 million times, the uncertainty of the result was finally quantified. Based on the results, the contribution rates of per capita income, population density, forest coverage rate, freshwater resources per capita and resources were always small, with the maximum values no more than 0.05. However, the gross industrial product, ratio of agricultural GDP, political index, agricultural land, Miami Index, number of people affected by extreme disasters and number of people who died from extreme disasters always had significantly higher weights in the model, with their maximum weights over 0.15. In terms of fluctuation, the coefficient of variation of freshwater resources per capita was the largest, whose value was 0.90 (the 17 indexes were in intervals between 0.8 and 0.9), and the fluctuation of the ratio of political index was the smallest, with a coefficient of variation of 0.2. The results show the model's reliability for entropy and AHP analysis to ensure the weight of different indexes. In further study, it will be possible to consider deleting indexes with small fluctuations and the small weights.

Considering the difficulty in acquisition of comprehensive data at the global scale, the national vulnerability assessment was conducted from 1996 to 2008 in this study. Change (1997) noted that years to decades can turn over capital stock responsible for emission of greenhouse gases. Thus, 12-year period studies can also reflect the effects of climate change and the adaptation of national laws in some way. However, due to the existence of social unrest and its abruptness, the return period of extreme disasters (Wu et al., 2017), and the economic cycle (Madhani, 2010) and its uncertainty (the length of the business cycle is inconclusive, with proposed periods including 40 months, 11 years, 20 years, 50 years, etc.), the 12-year study period can only represent some of the attributes of the entire cycle. Thus, a long-period study is needed in the future.

4. Conclusion

In this study, a comprehensive index framework was constructed for national vulnerability to climate change by including

sensitivity and adaptive capacity indicators. Then, a first spatial-temporal assessment of national vulnerability was conducted from the global perspective, covering 171 countries from 1996 to 2008. Based on the results, African countries were identified as hotspots of vulnerability and unstable countries in the changing climate and all 171 countries could be clustered into 8 groups based on their key influencing index on the national vulnerability. The average increasing rate of the vulnerability index was 0.30% during 1996–2008, indicating that the earth gained more vulnerability than invulnerability since 1996. The results of this new framework were consistent with those of the previous Fragile State Index and World Risk Index but provided more details and quantitative vulnerability analysis. For example, our results indicated that the vulnerability of Mexico was lower than that indicated by previous studies. Countries can take different measures based on the classification of spatial and temporal trends. The methods and results presented in this paper could be used as references for climate change adaption and policy at the global scale.

However, it should be noted that the acquisition of comprehensive data sets at the global scale is extremely hard. If other more detailed and longer-term data, such as species diversity at ecoregion level, could be obtained, we suggested a more acute tendency analysis could be conducted. Besides, lots of indictors and methods are available for risk evaluation and uncertainty analysis. Future researches are suggested to compare these methods from the global perspective.

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